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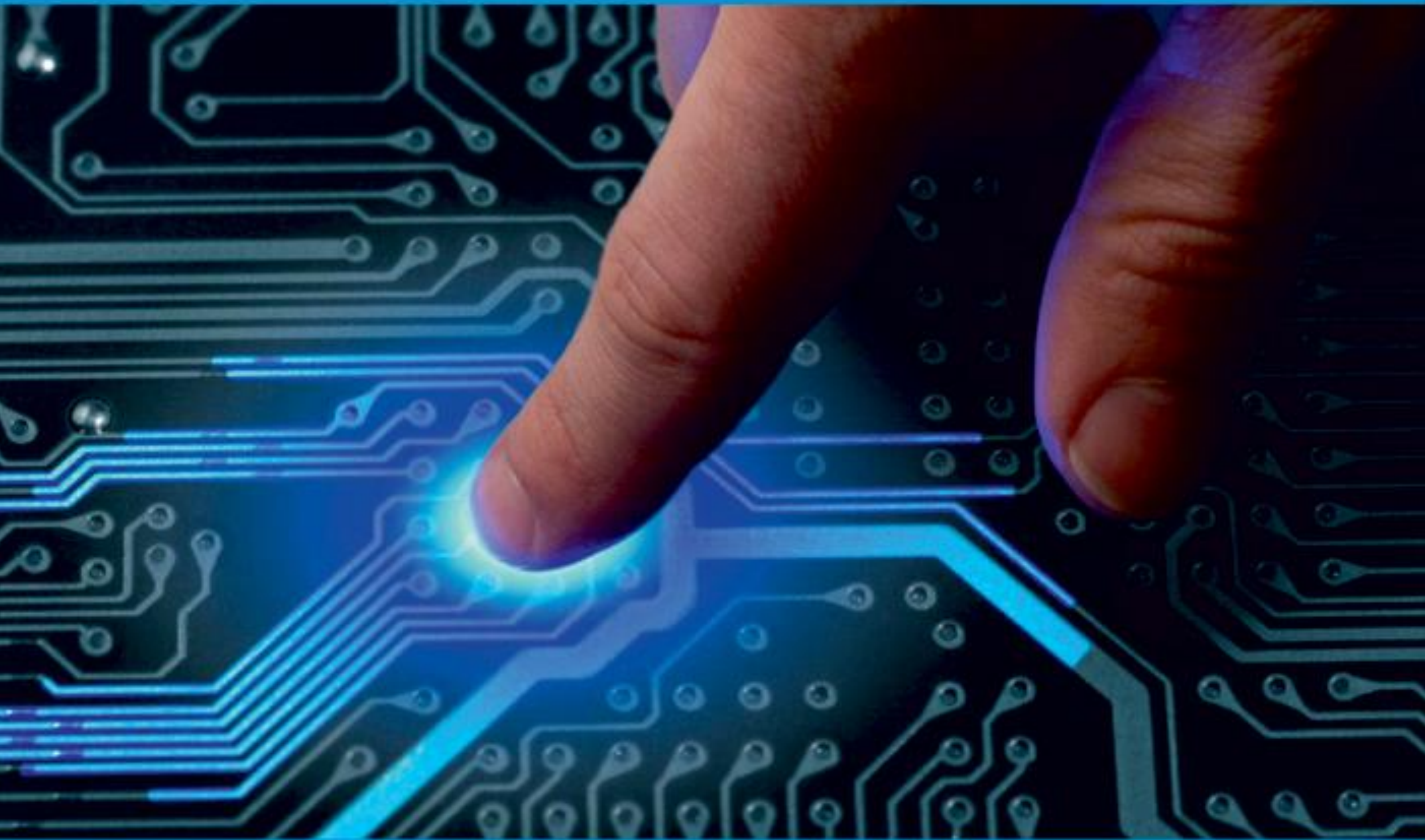

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Machine Learning for Estimate Crop Yield Recommendations System

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ABSTRACT: In agricultural production life, the protection of wheat yield is a top priority. Controlling wheat diseases is one of the important initiatives to protect wheat yield effectively protects wheat yield, therefore, disease identification of wheat is extremely critical to promote agricultural development. In recent years, with the continuous development and innovation of computer vision technology, the implementation of various plant disease detection has become more solvable. Deep learning has been commonly used in smart agriculture scenarios, and its models have the following characteristics Deep network models are very dependent on the dataset. The performance of the deep model can be improved by the attention mechanism. Most of the existing research focuses on recognition efficiency without paying attention to inference efficiency, which makes its application in practical production limited. Therefore, the dataset used in this paper is photographed from diseased wheat grown in the field, which has a more complex picture background than previous studies with high image resolution and many pixel points. This adds to the complexity of the features extracted by the neural networks in our study.

KEYWORDS: Convolution Neural Network, Deep learning model, Wheat crop disease, Image analysis, Performance evaluation

I. INTRODUCTION

Wheat is the second largest crop in the world, providing 19% of human caloric intake [1]. Wheat diseases greatly affect wheat production and cause significant wheat losses. At the current level of plant protection technology, annual wheat losses due to wheat diseases account for 26–30% of the theoretical wheat yield worldwide. In the absence of the application of plant protection technologies to manage farmland, wheat disease losses can account for up to 70% of the theoretical wheat yield [2]. Given that wheat leaves suffering from different kinds of diseases have certain differences, this is well suited to identify such differences and thus give diagnostic conclusions through computer vision-related methods. Nema et al. divided the collected images of wheat leaves into training and test datasets and tried to classify wheat leaf images by support vector machines to achieve differentiation between healthy wheat leaves and diseased wheat leaves [3]. Zhang et al. used the least squares discriminant support vector machines, K-nearest neighbor model and analysis model, and designed multiple sets of experiments to identify wheat grains with or without Fusarium spike blight. They chose hyperspectral images as training data, and the support vector machines achieved the best results on two images that were not used as training data [4].

In recent years, there have been studies on the application of computer vision techniques to the detection of wheat diseases. However, their training and test datasets are relatively small and the types of diseases that can be identified are single, and many of them research the issue through the method based on the support vector machine model. The drawback of support vector machines is that they require manual extraction of features from images. With the development of artificial neural networks, convolutional neural networks are becoming more and more mature. Using convolutional neural network techniques can avoid manual extraction of image features, which can reduce the burden of the researchers involved, which can make more researchers focus more on improving the accuracy of the model [5]. Convolutional neural networks are composed of many computational nodes and the nodes are arranged in the layer order. Each node in the previous layer generates data that is processed by an activation function and passed to each node in the next layer. When dealing with computer vision problems, images are often stored in RGB format. RGB images have three color channels and use a three-dimensional matrix to portray the image features [6].

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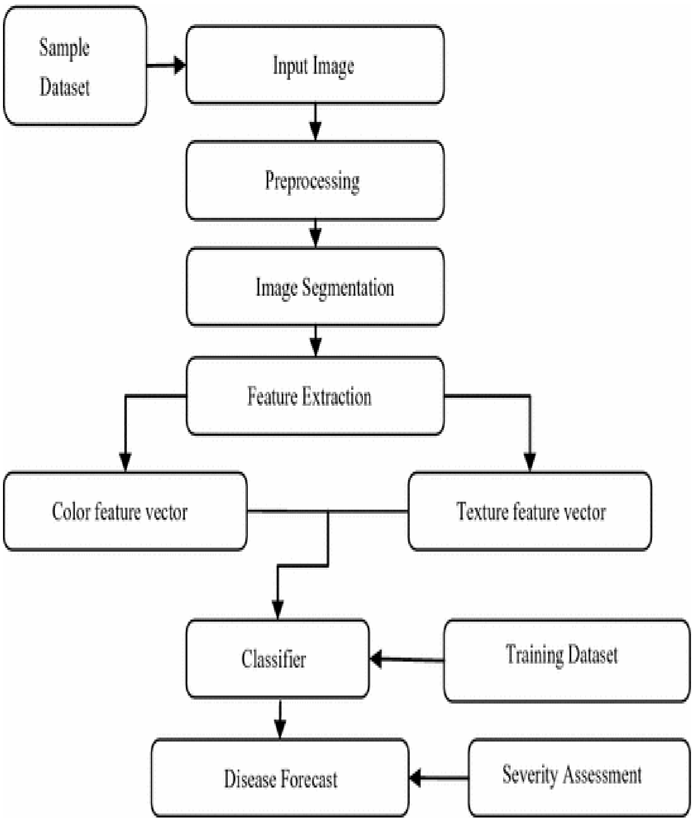

Fig 1: Work Flow Of Wheat Disease

Feature extraction is achieved through filters by acting on the matrix of features to be extracted. The presence of an activation function makes the 3D matrix of the original image and the matrix obtained by filter extraction, not simply linear [7]. By processing the images, the convolutional neural network can effectively perform the classification task. For wheat disease identification, data from the training set are input into the model, while the model weights are updated by backward transfer, and the predicted and expected values are used to calculate the error. After a limited number of epochs, the model and its parameters are saved, and the trained model can then be used to classify and detect a wide range of diseases.

II. RELATED WORK

Wheat is an essential crop providing food for billions of people worldwide. However, various diseases threaten its production and yield, which can significantly reduce the wheat crop's productivity. The Food and Agriculture Organisation says many people are undernourished due to a lack of food [1]. Early detection and timely management of these diseases are crucial to prevent crop losses and ensure food security. In this regard, image processing, artificial intelligence, machine learning, and deep learning algorithms have the ability to revolutionize the way for managing crop diseases in the agricultural field [2]. Using these techniques to give precise and timely details regarding the kind and severity of diseases affecting wheat crops can help farmers make informed decisions about disease management and prevent crop losses. Additionally, these techniques can monitor crop health over large areas, allowing for more efficient and effective disease management strategies.

Furthermore, this discrepancy can be attributed to the farmer's access to more sophisticated equipment, information, and techniques. Various machine learning methods, including Decision Tree Techniques, Support Vector Machine Learning, Random Forest Models, K-Means clustering, Artificial Neural Networks, Convolutional Neural Networks, etc., have been used to identify and categorize various crop diseases. Alternative algorithms have been outperformed by techniques like decision trees and support vector machines. In this regard, Pranjali et al. [3] discuss plant leaf disease detection with the help of a support vector machine algorithm. A deep learning method-based multifunctional mobile application for plant disease detection was proposed by Uzhinskiy et al. [4].

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An innovative framework for identifying a wheat-related illness that uses several more profound instances of learning and deals with crop images without any professional preprocessing was created by Lu et al. [5]. Zhu et al. [6] proposed machine learning-based dissimilarity between observed and simulated wheat yield shock data call for improvement in crop models. Jahan et al. [7] used machine-learning techniques to detect and classify wheat diseases. Further, Azadbakht et al. [8] also used the ML technique to recognize the rust in wheat leaves was investigated at the canopy size and LAI level. A practical ML-based framework for the automatic recognition and classification of various types of wheat diseases was discussed by Khan and Habib et al. [9].

The seriousness of wheat white powdery, as reported by [10] Khan and Imran Haider et al., was characterized using a machine learning-based chromatic analysis of images with a hyperspectral technique. The diagnosis of fusarium head blight in semolina wheat was investigated by Azimi et al. [11] used arithmetic and machine learning methods. Accurately detecting wheat diseases and prescribing the appropriate remedial actions can help farmers maximize their profits by minimizing crop losses, improving crop yields, and reducing costs. Recently, deep learning has been a powerful tool for detecting and classifying diseases in wheat crops. Convolutional Neural Networks (CNNs), such as deep learning techniques, have greatly improved image-based disease detection and classification accuracy and reliability.

III. METHODS

An automated search technique was used in MnasNet to create the model structure. The network search algorithm was utilized to automatically explore a diverse range of potential model structures by selecting an optimal combination from convolutional layers, expanded convolutional layers, pooling layers, and other modules for network construction. Additionally, each module's hyper-parameters were determined by the search algorithm automatically, facilitating the rapid establishment of an effective network structure in MnasNet. Moreover, MnasNet incorporates a platform-aware approach to enable model tuning for diverse hardware platforms. The network structure and hyper-parameters can be automatically modified based on varying computational resources and memory constraints, ensuring optimal performance across different devices.

Secondly, it utilized progressive learning to gradually increase the network's width and depth while dynamically adjusting the relationship between regular scale and input image size as required. To optimize resource utilization and enhance performance, additional modules, such as fused mobile inverted bottleneck convolution (Fused-MBConv), were integrated into EfficientNetV2. These modules ranged in depth from 2 to 6 and facilitated the development of deeper networks. Furthermore, EfficientNetV2 demonstrated superior adaptability across devices with varying processing complexities and input image sizes by outperforming several state-of-the-art models in common image classification tasks.

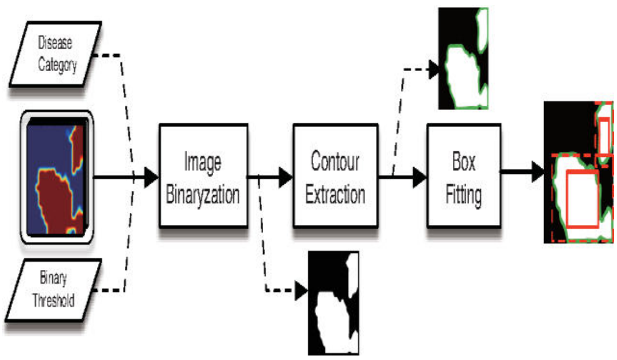

Fig 2: network architecture search (NAS)

On the basis of the V2 series, the block module was updated in the model design, and the attention mechanism squeeze excitation (SE) module was added. By reorganizing the structure of the time-consuming layer using network architecture search (NAS) search, the 32 convolution kernels of the first convolution layer were reduced to 16, simplifying the last stage. The swish activation function was revised, which evolved from the ReLU activation function, thus creating the h-swish activation function. In terms of recognition accuracy, latency reduction, and detection speed, MobileNetV3 improved the performance of classification, detection, and segmentation to a greater

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extent than its MobileNet family ancestors. A confusion matrix is a table summarising how well a classification model performed regarding correct and incorrect predictions. It is a helpful tool for assessing the accuracy of the model's predictions. A table to compare the predicted and actual values. These components can compute several metrics, such as accuracy, precision, recall, and F1 score, providing valuable insights into the model's performance. The confusion matrix is frequently employed in binary classification issues but can also be expanded to multi-class problems.

IV. RESULTS AND DISCUSSION

The Largest Wheat Disease Classification Dataset (LWDCD2020) with Fusarium head blight, healthy wheat, leaf rust, and the tan spot is a publicly available dataset designed to evaluate deep learning models for classifying wheat plant diseases. The dataset consists of images of wheat leaves captured from the field under natural lighting conditions These algorithms can analyze large amounts of data and help recognize patterns indicative of different diseases affecting wheat crops. CNNs are widely used for image analysis, making them well-suited for automatically identifying and classifying wheat diseases. CNN is a deep learning algorithm commonly used for image recognition and computer vision tasks. Haider et al. [12] discussed a general approach for quickly recognizing and categorizing diseases affecting wheat crops using decision trees and CNN techniques.

In this study, the images of wheat stripe rust and powdery mildew as well as healthy wheat leaves were obtained through field shooting and network acquisition, which were used to create datasets. The images from field shooting were manually captured with a 48-megapixel mobile phone in the open environment with a complex background of natural light during the 2022–2023 period in the Ili Kazakh Autonomous Prefecture and the Bayingoleng Mongolian Autonomous Prefecture, Xinjiang, which are the main wheat-producing regions. The wheat in these sampled areas is grown according to local conventional cropping patterns. Each image was manually annotated after being examined by a phytopathologist.

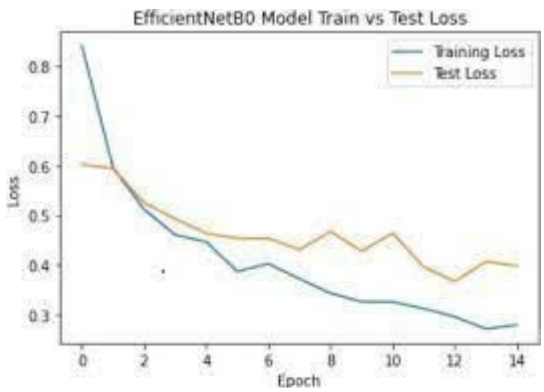

Fig 3: Result Analysis of wheat crops using decision trees and CNN techniques

When a deep learning model is trained using a distinct training dataset, evaluation metrics are used to evaluate its performance on data that has yet to be seen. In a model considering the remaining 25% of unseen data, several metrics can be used to assess its performance. Such as, Accuracy, Precision, Recall, and F1-score. Accuracy is the proportion of accurate predictions obtained by the model based on unobserved data. Precision is the percentage of samples in which the model correctly predicted a positive result, Recall counts the number of genuinely positive pieces, and the mean value of Recall and precision is the F1 score.

V. CONCLUSION

With further improvements in data collection and the development of various disease detection, deep learning models have become an effective tool for precision agriculture, enabling farmers to make informed decisions and improve crop yields. Overall, applying deep learning models in agriculture help to increase food security, reduces waste, and improves sustainability in the long run. Hence, in this paper, a deep learning models for detecting and classifying wheat diseases is developed. The proposed method using the ResNet152 model shows promising results in detecting and classifying different types of wheat diseases, which can help farmers to take timely action to prevent crop damage and ensure a healthy harvest. It provides several advantages, such as high accuracy in identifying diseases affecting wheat

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crops and fast processing speed. The proposed model achieves a high testing accuracy of 93.27%, whereas the training accuracy is 97.81%. However, further research is needed to assess the model's performance on larger datasets and in different environmental conditions.

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